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Macroeconomic Nowcasting and Forecasting with Big Data

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monitoring economic conditions, business cycle analysis, high-dimensional data, real-time data flow

Abstract

Data, data, data. . . . Economists know their importance well, especially when it comes to monitoring macroeconomic conditions—the basis for making informed economic and policy decisions. Handling large and complex data sets was a challenge that macroeconomists engaged in real-time analysis faced long before so-called big data became pervasive in other disciplines. We review how methods for tracking economic conditions using big data have evolved over time and explain how econometric techniques have advanced to mimic and automate best practices of forecasters on trading desks, at central banks, and in other market-monitoring roles. We present in detail the methodology underlying the New York Fed Staff Nowcast, which employs these innovative techniques to produce early estimates of GDP growth, synthesizing a wide range of macroeconomic data as they become available.

> [O]nly by analyzing numerous time series, each of restricted significance, can business cycles be made to reveal themselves definitely enough to permit close observation.
>
> —Burns & Mitchell (1946, p. 11)

1. INTRODUCTION

For more than a century, government agencies and private institutions have been collecting and organizing information on many facets of the economy, and over time, the scope of data collection has grown and the quality of data has improved. Today, macroeconomic data are released to the public on a regular schedule: Almost every day, new data become available and are analyzed, commented on, and interpreted. Real-time monitoring of macroeconomic conditions has become the full-time job of dedicated economists at central banks, at government agencies, and in the corporate world; these economists sift through big and complex macroeconomic data to distill all relevant information. Releases that come out as surprises move markets, sometimes significantly, as investors reassess their expectations about the state of the economy.

Although the term big data typically conjures up the image of data collected via the Internet about individual habits related to consumption and social media, big data presented a challenge to macroeconomists well before the collection of more granular data became pervasive in other disciplines. From the pioneering search for patterns and regularities in the data that led Burns & Mitchell (1946) to identify the business cycle and the parallel effort of Kuznets to build the National Income and Product Accounts (NIPAs), to the vast array of expert data collection and analysis done today, macroeconomists have embraced the big data challenge, pushing the frontier of statistical methods and refined measurement.

New methodologies in time-series econometrics developed over the past two decades have made possible the construction of automated platforms for monitoring macroeconomic conditions in real time. Giannone et al. (2008) build the first formal and internally consistent statistical framework of this kind by combining models for big data and filtering techniques. Because of the emphasis on the present, they dub this framework nowcasting, a term originally used in meteorology for forecasting the weather occurring in the next few hours.

As an illustration of nowcasting with big data, this review describes in some detail the New York Fed Staff Nowcast. This platform was introduced to the public in April 2016 (Aarons et al. 2016). Its estimates of GDP growth for the current and subsequent quarter, based on data released over the course of each week, are made available every Friday at 11:15 a.m. on the Federal Reserve Bank of New York's public website (**www.newyorkfed.org/research/policy/nowcast**). This nowcasting model extracts the latent factors that drive movements in the data and produces a forecast of each economic series that it tracks: When the actual release for that series differs from the model's forecast, this news impacts the nowcast of GDP growth. This approach formalizes key features of the way in which market participants and policy makers have traditionally produced forecasts, a process that involves monitoring many data releases, forming expectations about them, and then revising the assessment of the state of the economy whenever facts differ from those expectations. The model combines in a unified framework a variety of approaches developed over time for monitoring economic conditions.

Figure 1, which we discuss in detail in Section 5, illustrates the evolution of the nowcast of real GDP growth for 2016:Q4. The figure shows the weekly updates of the nowcast, i.e., the predictions of the model based on the information available at the dates indicated on the horizontal axis. Their progression reflects how the news in the data released each week changes the nowcast for that week. The impact on the nowcast of news from a week's data releases is visualized by the colored bar of that week, where the colors identify the categories of the data releases, as indicated

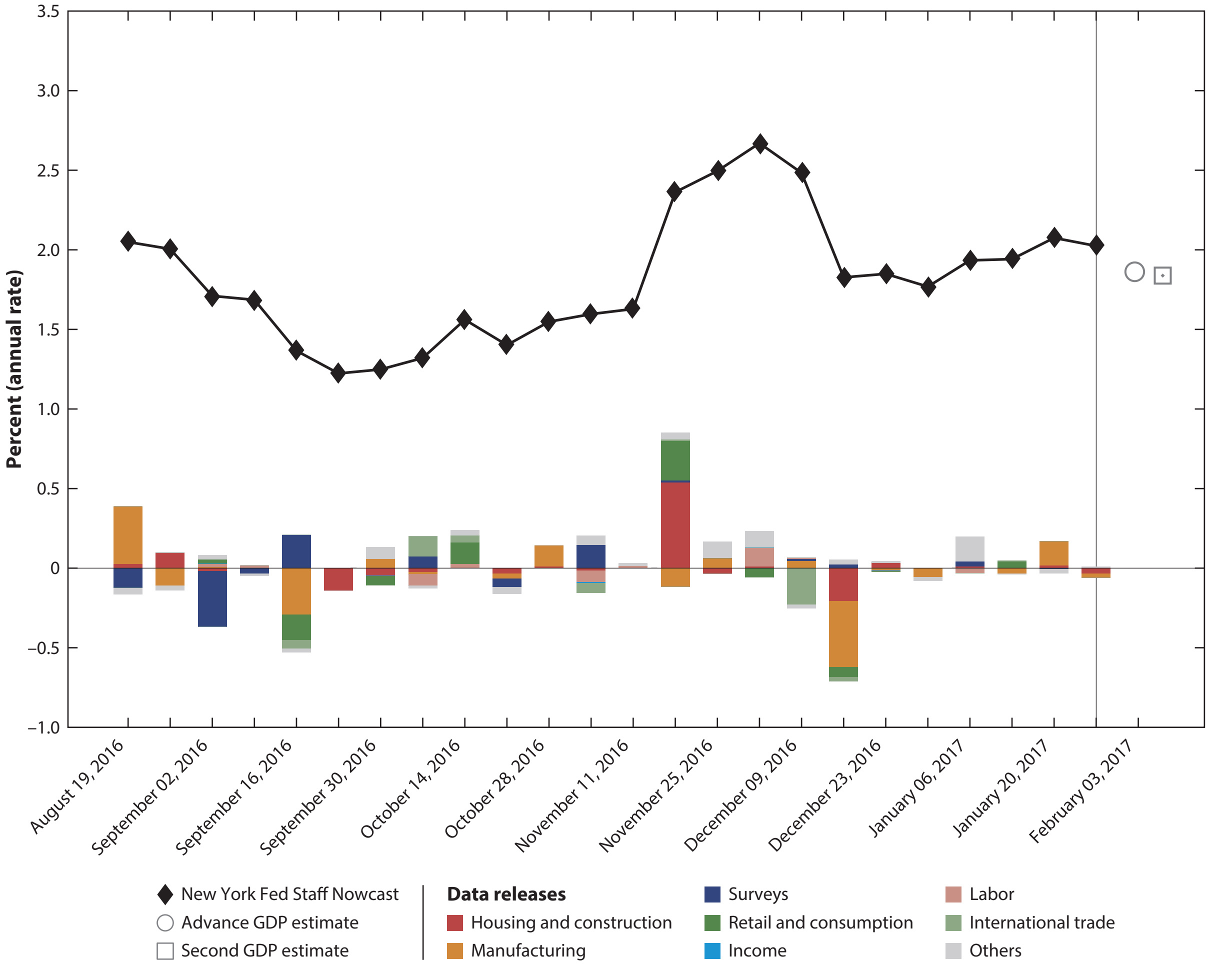


Figure 1

The New York Fed Staff Nowcast for 2016:Q4 (see also **Figure 4**). Figure created using the Federal Reserve Bank of New York, Nowcasting Report, March 3, 2017 (**https://www.newyorkfed.org/research/policy/nowcast**).

in the legend. For example, on November 11, the nowcast of real GDP growth for the fourth quarter of 2016 was 1.6%; a string of positive surprises during the following week, primarily from consumption data and housing market data, only partially offset by negative surprises from manufacturing data, increased the nowcast to 2.4%.

Before moving to a detailed description of the nowcasting model employed at the Federal Reserve Bank of New York, we review in Section 2 the variety of methods developed over time to monitor macroeconomic conditions. We then discuss issues of data collection and measurement, with an emphasis on the nature of macroeconomic time-series data and their real-time flow (Section 3). In Section 4, we present the econometric framework for nowcasting with a large data set, focusing on the parsimonious aspect of the dynamic factor model methodology. In Section 5, we dig into the specifics of the New York Fed Staff Nowcast. Section 6 concludes.

2. MONITORING ECONOMIC CONDITIONS

Every day, economists parse the trove of economic data released by statistical agencies, private and public surveys, and other sources to assess the health of the economy. Separating meaningful signals from noise is not an easy task, and several approaches have been developed and applied over time to tackle it. These range from detecting business cycle turning points and constructing indexes of economic activity to forecasting comprehensive measures of the state of the economy with formal models and judgment.

The first systematic analysis of economic fluctuations dates back to Arthur Burns and Wesley Mitchell, the economists who pioneered business cycle analysis at the National Bureau of Economic Research (NBER) in the late 1930s. Faced with the complexity of the economic system, Burns & Mitchell (1946) attacked their investigation as a big data problem: They scrutinized hundreds of data series in search of patterns and regularities.[1] What they uncovered was a systematic comovement among the series and a pervasiveness of fluctuations across different sectors and different kinds of economic activities. This led them to identify the broad recurrence of two states in the economy: expansions and recessions. Thus, they defined the business cycle as the "type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions" (Burns & Mitchell 1946, p. 3). What makes Burns & Mitchell's work so important and innovative is the fact that the pattern they were looking for was unknown—in modern language, we would call it unsupervised classification. We could argue that their careful screening for pattern recognition is what, many decades later, became machine learning.

Pervasiveness in the movement of various indicators (across sectors and activities) remains central to the definition of business cycles currently used by the NBER Business Cycle Dating Committee: "During a recession, a significant decline in economic activity spreads across the economy and can last from a few months to more than a year. Similarly, during an expansion, economic activity rises substantially, spreads across the economy, and usually lasts for several years" (**www.nber.org/cycles/recessions.html**).

In a modern context, determining business cycle turning points from a variety of series can be seen as a two-step process: first identifying turning points in each of the large variety of data series and then constructing reference turning points based on the distribution of the individual series' turning points. The first step was initially based on judgment and was later automated by Bry & Boschan (1971). The identification of clusters of turning points to determine aggregate turning points has been formalized by Harding & Pagan (2006, 2016) and Stock & Watson (2010, 2014).

The dating of the business cycle represents one of the most common and robust summaries of the economy, widely understood not only by experts, but also by the public at large. The NBER Business Cycle Dating Committee today continues the work of Burns and Mitchell, determining the official turning points in the US economy. It examines and compares the behavior of a variety of broad and comprehensive economic activity measures, primarily real GDP and, most recently, real gross domestic income, employment, and industrial production, together with other less broad but highly informative indicators to determine when a recession starts and when it ends.

[1] Burns and Mitchell classified 71 out of the original 487 economic time series as the most trustworthy indicators of business cycle revivals: "we have drawn up a list of statistical series differing widely in other respects but alike in that each has in the past proved to be a fairly consistent indicator of cyclical movements in general business. We regard this list not as a 'forecasting' machine, but rather as a registering device that may be useful to those who are trying to interpret the general drift of current fluctuations in different types of business activity" (Mitchell & Burns 1938, p. 1).

Monitoring a large number of different variables can enhance timeliness and accuracy in assessing the health of the economy: It not only enables one to exploit different sampling frequencies and different timing of macroeconomic data releases, but also mitigates the risk of overweighting idiosyncratic fluctuations, as well as measurement errors. However, since many indicators move together over the cycle, the behavior of multiple series providing a similar signal can be well summarized with low-dimensional indexes, which can be broadly considered as indexes of business cycles.

Indexes of economic activity, such as the leading, coincident, and lagging indicator indexes for the US economy constructed by the Conference Board, are in this tradition. The Organisation for Economic Co-operation and Development (OECD) also publishes a composite leading indicator index for 21 member countries and three zone aggregates (OECD 2012), and for the euro area, the Conference Board publishes coincident and leading indicators (for a survey of indexes of economic indicators, see Marcellino 2006). More recently, indexes of economic indicators have been constructed using dynamic factor models, which, as we argue at length in Section 4, amounts essentially to using model-based aggregation schemes. The use of factor models for the construction of business cycle indexes was pioneered by Stock & Watson (1989).

From an econometric perspective, the use of factor models to monitor macroeconomic conditions stems from the basic insight that information about different aspects and sectors of the economy can be considered as an imperfect measure of a latent common business cycle factor. A robust finding of this literature is that a few common factors can capture the salient features of business cycle fluctuations. First documented by Sargent & Sims (1977), this result has more recently been confirmed with high-dimensional macroeconomic data, as shown by Giannone et al. (2004) and Watson (2004).

Vector autoregression (VAR) models are also widely used in macroeconomics to jointly model the dynamics of economic variables. In these very general linear models, every variable depends on its own past and on the past of each of the other variables, and the pattern of correlation of the forecast errors in different variables is left unconstrained. In Bayesian VARs (BVARs), this high level of complexity is combined with a naive prior model that assumes that all the variables are independent white noise or random walks. BVARs have been advocated for by the earliest proponents of VAR models in economics (Doan et al. 1984, Sims 1980). Recent research has shown that they are strictly connected with factor models and are suitable for the analysis of big data (Bańbura et al. 2010, De Mol et al. 2008).

Economists also focus on some key and comprehensive indicators of economic activity, such as real GDP growth. Indeed, the business cycle turns out, ex post, to be very close to the peaks and troughs of this single comprehensive measure of economic activity (see, e.g., Hamilton 1989, Harding & Pagan 2002). Moreover, the journalistic definition of a recession as two consecutive quarters of negative real GDP growth is a popularized version of algorithms derived to identify business cycle turning points that bridges business cycle analysis and the careful work dedicated to the construction of GDP data in the NIPAs, as we discuss in Section 3. However, since comprehensive measures are available only with a delay, it is customary for economists to make predictions for the official figures while waiting for their release, pooling information from a variety of economic series.

Forecasting is essential to central banks in informing their policy decisions and communicating their economic outlook to the public. Central bank staff typically use a suite of models and a fair amount of expert judgment to arrive at their forecasts.[2] Businesses and consumers, lacking individual expertise, also rely on forecasts by professional economists to inform their spending and investment decisions.

[2]Sims (2002) provides an insightful review and assessment of the forecasting activity at several major central banks.

The collection of expert forecasts has a long tradition. The oldest quarterly survey of macroeconomic forecasts is the Survey of Professional Forecasters (SPF), which began in 1968 and is currently conducted by the Federal Reserve Bank of Philadelphia.[3] Forecasters provide quarterly projections of US GDP growth and measures of inflation, unemployment, and payroll employment for the current quarter and subsequent four quarters, as well as annual projections for the current and following years.[4]

Professional forecasters typically use a combination of approaches for forecasting. A special survey conducted by the Real-Time Data Research Center at the Federal Reserve Bank of Philadelphia in 2009 revealed that the majority of the SPF panelists use mathematical models to form their projections but also apply subjective adjustments to their model-generated forecasts. Interestingly, the use of models is predominant for short-horizon forecasts and less common for long-horizon projections. However, not all forecasters monitor economic conditions at high frequency: Only 5 out of 25 respondents updated their forecasts at higher than monthly frequency.

Alongside professional forecasters, market analysts also strive to understand where the economy currently is and to forecast in which direction it is going. They track major data releases to detect early signals: News in the data, relative to their expectations, leads them to update their projections. Market forecasts are also collected in surveys, of which a popular example is the one conducted by Bloomberg. When releases come out as surprises, they move markets (Bartolini et al. 2008, Gürkaynak & Wright 2013, Gürkaynak et al. 2005). In fact, macroeconomic surprises explain a large part of asset price fluctuations.[5] This evidence suggests that investors continuously update and reassess their expectations about the future path of the economy and the policy reaction based on macroeconomic news.

How successful are professional forecasts? Apparently, there is little predictability of real GDP growth beyond the current and next quarter, as shown in **Table 1**, which reports the SPF forecast error statistics alongside those of a naive statistical model: The big gain of SPF forecasts is at horizon 0 (the forecast of the current quarter). For reference, the table also includes the root mean square error of the Bureau of Economic Analysis (BEA)'s advance GDP release assessed relative to its most recent revised value.

Forecasts appear to be most helpful when one wants to understand where the economy is now, but predicting the present requires tracking a large and complex set of data as it becomes available continuously in real time. Traditionally, this was achieved using a combination of data scrutiny, a variety of simple models, and expert judgment. As discussed in Section 1, over the past two decades, new methodologies in time-series econometrics have made possible the development of platforms for real-time forecasting that combine formal models for big data and filtering into nowcasting. The model we describe in this review is one such platform that we would argue unifies several analytical approaches for monitoring current economic conditions that are typically used

[3]The survey was initially conducted by the American Statistical Association (ASA) and NBER and was known as the ASA-NBER Survey (see Zarnowitz 1969). The survey was taken over by the Federal Reserve Bank of Philadelphia in 1990.

[4]Another old survey is the Livingston Survey, started in 1946 and currently run by the Federal Reserve Bank of Philadelphia. This survey is semiannual and consists of forecasts of 18 different quarterly and monthly variables describing national output, prices, unemployment, and other macroeconomic data. Also, since 1999, the European Central Bank has run a Survey of Professional Forecasters similar to the US survey that collects expectations for the rates of inflation, real GDP growth, and unemployment in the euro area for several horizons, together with a quantitative assessment of the uncertainty surrounding them. In addition to other private surveys, such as those of Blue Chip and Consensus Economics, several institutions, such as the OECD and the International Monetary Fund, communicate and summarize their economic outlook by publishing forecasts.

[5]Altavilla et al. (2017) show that these surprises explain up to one-third of the quarter-to-quarter fluctuations in government bond yields.

Table 1 Forecast errors for GDP at different horizons

	RMSE					
Horizon (quarters ahead)	**−1**	**0**	**1**	**2**	**3**	**4**
BEA[a]	1.61					
Naive AR model[b]		2.43	2.46	2.55	2.55	2.55
SPF[c]		1.94***	2.21**	2.40	2.47	2.52

Root mean square errors (RMSEs) for GDP forecasts at horizons 0 (i.e., nowcast) to 4 quarters ahead. Errors are computed on the evaluation sample 1985–2014 as the difference between the latest available GDP estimate and three types of GDP projections. *** and ** indicate SPF forecasts that are significantly more accurate than those of the naive AR model at the 1% and 5% levels, respectively, based on Diebold-Mariano tests with a quadratic loss function. Table created using the authors' calculations and data from the Bureau of Economic Analysis (BEA) and Federal Reserve Bank of Philadelphia.
[a]The first official (also known as advance) estimate published by the BEA at the end of the month following the quarter under consideration. This is a projection produced with a 1-month delay, as indicated by the −1 in the column heading.
[b]Refers to iterative forecasts from an autoregressive (AR) model calculated by the Federal Reserve Bank of Philaldelphia.
[c]Based on the median forecasts from the Forecast Error Statistics for the Survey of Professional Forecasters (SPF) (for more details, see **https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files/error-statistics**).

independently. As do indexes of coincident and leading indicators, our model characterizes current economic activity by condensing the information into a few factors that summarize business cycle conditions. The model mimics the behavior of market participants and professional forecasters by tracking all relevant measures of economic activity, making predictions that are constantly updated in response to unexpected developments in economic releases. The general finding is that these automated forecasts are as accurate as, and highly correlated with, the forecasts produced by institutions and experts.

Unlike the methods of professional forecasters, who combine a variety of unrelated models and apply some form of judgment, using a single formal model allows for a transparent and internally coherent analysis of the real-time data flow. The model, in essence, codifies within an econometric framework the best practice and expert knowledge in business cycle analysis. This is a significant change in paradigm that is well summarized by Stock & Watson (2017).[6]

3. BIG DATA AND THE REAL-TIME INFORMATION FLOW

Parallel to the development of various ways of monitoring economic conditions described above is the advancement of measurement. The efforts to collect a very large and complex set of measurements on the economy and to organize and synthesize them in a system of coherent aggregates—the national accounts—were first undertaken during the Great Depression, at the same time that macroeconomics emerged as an independent discipline. If macroeconomics was the answer to the challenges posed to economics by the events of the Great Depression, national accounting was its counterpart in the realm of economic measurement. In the United States, Simon Kuznets

[6]"Twenty years ago, economists who monitored the economy in real time used indexes of economic indicators and regression models for updating expectations of individual releases . . . combined with a large dose of judgment based on a narrative of where the economy was headed. While this approach uses data, it is not scientific in the sense of being replicable, using well-understood methods, quantifying uncertainty, or being amenable to later evaluation. Moreover, this method runs the risk of putting too much weight on the most recent but noisy data releases, putting too little weight on other data, and being internally inconsistent because each series is handled separately . . . . The current suite of tools for handling large series and complicated data flows . . . using a single model to evaluate these releases—rather than a suite of small models or judgment—provides a scientific way to use the real-time data flow" (Stock & Watson 2017, p. 71).

developed the NIPAs to provide a comprehensive picture of what was happening in the economy during that time of crisis, as well as to monitor the effect of the many policies put in place by President Roosevelt to fight the Depression. Subsequently, the NIPAs became a crucial tool in the efforts to transform the economy in support of the war effort (for more details, see Landefeld et al. 2008).

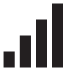
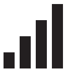
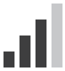
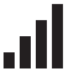
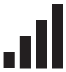
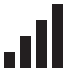
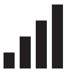
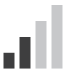
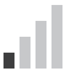
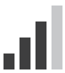
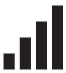
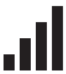
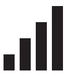
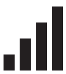
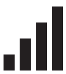
Currently, academic analysis largely focuses on a few macroeconomic aggregates that comprise the national accounts, such as GDP, consumption, or investment. These time series result from a complex and systematic effort to measure all the economic activity taking place in the US economy within a formalized and coherent framework. Conceptually, this framework is based on accounting principles, rather than on statistical or economic models, but it too is a formalized answer to a big data challenge: how to describe and track over time the evolution of a complex and continually evolving system like the US economy.

For GDP, the most representative and cited of all macroeconomic variables are the benchmark estimates produced by the BEA every 5 years based on an economic census that covers virtually all of the roughly seven million businesses with paid employees in the United States and over 95% of the expenditures included in GDP. Economic data hardly get any bigger than this! Between these benchmark estimates, which provide an accurate, comprehensive, and detailed snapshot of the US economy, annual and quarterly estimates are based on surveys also conducted by the US Census Bureau, with about 150,000 and 35,000 reporting units, respectively, as well as on administrative data (for instance, from the Internal Revenue Service) and extrapolations based on past patterns or other source data [for instance, employment, hours, and earnings data from the Bureau of Labor Statistics (BLS)]. This process, whereby very detailed microeconomic information is aggregated into a coherent set of national accounts, produces a regular stream of GDP estimates and subsequent revisions. After the first, or advance, quarterly estimate, released about 1 month after the end of the quarter in question, second and third quarterly estimates are released in the subsequent months, and comprehensive revisions, which incorporate methodological advances that update the accounts to reflect changes in the economy, ultimately follow.

One of the primary considerations in the design of this release schedule, and of the data collection efforts that underpin it, is the trade-off between accuracy on the one hand and timeliness and frequency of estimates on the other. Maximum accuracy is achieved with the benchmark releases, since they are based on a census, but they are only carried out every 5 years. At the other extreme, the advance release is available every quarter and with less than a month's delay, but only about half of the included expenditures data reflect survey-based information for all 3 months of the quarter. The rest is based on information for 2 months and on extrapolations. As a result of these statistical shortcuts, which are the inevitable cost of a timely release, the initial estimates are subject to potentially sizable revisions as more comprehensive and reliable information is folded into the accounts.

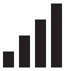
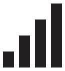
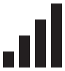
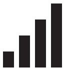
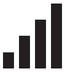
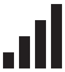
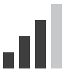
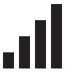
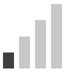
The statistical imprecision inherent in the quarterly GDP estimates, together with the fact that even the first estimate is only available with a delay of nearly a month, poses a significant challenge to policy makers and other observers with an interest in monitoring the state of the economy in real time. As a result, as we discuss in Section 2, most of these observers rely on alternative indicators of the health of the economy that become available over the course of the quarter to form a real-time view of economic developments. **Table 2** contains a list of the releases by both government agencies and private institutions that contain the most widely followed of these indicators. These releases are followed closely not just by economists, but also by market participants, people in business, and the media. The bars in the first column of the table provide a measure of the relevance of each release based on the percentage of Bloomberg users who subscribe to related alerts.

Table 2 Macroeconomic data releases

Relevance[a]	Release	Publication timing	Delay (days)[b]	Delay	Source
	Construction Spending	First business day of the month	2 months prior	33	Census Bureau
	ISM Manufacturing Report on Business	First business day of the month	1 month prior	3	ISM
	ISM Non-Manufacturing Report on Business	Third business day of the month	1 month prior	5	ISM
	US International Trade in Goods and Services	First full week of the month	2 months prior	35	BEA, Census Bureau
	Manufacturers' Shipments, Inventories, and Orders	First week of the month	2 months prior	35	Census Bureau
	ADP National Employment Report	First Wednesday of the month	1 month prior	5	ADP
	Employment Situation Report	First Friday of the month	1 month prior	7	BLS
	Manufacturing and Trade Inventories	First full week of the month	1 months prior	44	Census Bureau
	Job Openings and Labor Turnover	Second week of the month	2 months prior	42	BLS
	US Import and Export Price Indexes	Middle of the month	1 month prior	13	BLS
	Retail Trade	Ninth business day of the month	1 month prior	14	Census Bureau
	Producer Price Index	Middle of the month	1 month prior	14	BLS
	Wholesale Trade	Middle of the month	2 months prior	37	Census Bureau
	Empire State Manufacturing Survey	15th day of the month	Current month	−14	Federal Reserve Bank of New York
	Manufacturing Business Outlook Survey	Third Thursday of the month	Current month	−11	Federal Reserve Bank of Philadelphia

(Continued)

Table 2 *(Continued)*

Relevance[a]	Release	Publication timing	Delay (days)[b]	Delay	Source
	Industrial Production and Capacity Utilization	Middle of the month	1 month prior	17	Federal Reserve Board
	Consumer Price Index	Middle of the month	1 month prior	18	BLS
	New Residential Construction	12th business day of the month	1 month prior	16	Census Bureau
	Advance Economic Indicators	Last week of the month	1 month prior	28	Census Bureau
	New Residential Sales	17th business day of the month	1 month prior	26	Census Bureau
	Advance Durable Goods	Third week of the month	1 month prior	26	Census Bureau
	Personal Income and Outlays	Last week of the month	1 month prior	30	BEA
	Gross Domestic Product	Last week of the month	Prior quarter	28	BEA
	Productivity and Costs	First week of the month	Prior quarter	34	BLS

List of all the macroeconomic data releases used in the New York Fed Staff Nowcast. Releases are ordered based on their time of publication within the calendar month. Abbreviations: ADP, Automatic Data Processing; BEA, Bureau of Economic Analysis; BLS, Bureau of Labor Statistics; ISM, Institute for Supply Management.

[a]The bar graphs indicate the importance of each release according to the Bloomberg relevance index.

[b]The delay of each release is computed relative to the end of the reference period based on the 2017 calendar.

Perhaps the most prominent among these releases is the BLS's Employment Situation Report, which is issued on the first Friday of every month, as described in the third column of **Table 2**. This report, which includes data on payroll employment, unemployment, earnings, and many other aspects of the labor market, is of independent interest because it provides an in-depth picture of a particular segment of the economy that is not covered in as much detail in the national accounts. Yet the nature of business cycles, in which most sectors of the economy tend to move together, implies that good news for the labor market—or for manufacturing, construction, retail trade, and so on—usually reflects good news for the economy as a whole. Therefore, the information in the Employment Situation Report, along with that contained in all the other releases listed in **Table 2**, can be used to extract a signal on the current overall level of economic activity well before the first GDP estimate is available.

Of course, this exercise is subject to a trade-off between accuracy and timeliness, similar to the one we discuss above in relation to the successive GDP releases. None of the releases listed in **Table 2** is quite as comprehensive in its coverage of economic activity as the NIPAs. Moreover, the surveys underlying the releases vary widely in size and, thus, in statistical reliability. In general, indicators released closer to their reference period are bound to be less accurate. Therefore, no one indicator can be a silver bullet that solves the problem of accurately tracking the evolution of the economy in real time. A more promising approach is, instead, combining the information contained in the many available releases. Given the number of these releases, and the hundreds of statistics that they often include, designing such an approach is once again a big data challenge, essentially the same one faced by Kuznets in developing the NIPAs: how to synthesize the complexity of the US economy through one summary statistic. GDP provides an answer to this question based on accounting principles. Nowcasting addresses the same challenge through statistical modeling, as we discuss in detail in Sections 4 and 5.

In principle, the nowcasting solution to this problem is straightforward. The data are summarized through a few common factors the evolution of which is tracked in real time via filtering techniques. In practice, however, the implementation of this idea is complicated by the intricate nature of the information being tracked. As shown in **Table 2** , economic indicators are released on a nearly continuous basis over the course of a quarter. This trickling of information over time is often referred to as the data flow, but it is actually less smooth than the term might suggest, although it does follow an entirely predictable calendar. The earliest available information for the national economy on any given quarter is provided by the Institute for Supply Management Manufacturing Report for the first month of that quarter, which is released on the first business day of the following month (third row in **Table 2**). On the same day, the Census Bureau's Construction Spending Report is also made available (second row of **Table 2**), but, unlike the ISM report, it refers to 2 months prior. Therefore, it does not carry relevant information for the current quarter until the third month of the quarter. Similar considerations hold for the International Trade and Manufacturers' Shipments Report. Next to be released are two closely followed reports on the labor market. The most important is the above-mentioned Employment Situation Report by the BLS, which is released on the first Friday of every month. Since 2006, this report has been preceded on Wednesday by the Automatic Data Processing (ADP) National Employment Report. ADP is a large private payroll processing company that has assembled a nationally representative sample of firms among its clients, which allows it to estimate total payroll employment. From its relatively short track record, the ADP payroll estimate appears to be noisier than that produced by the BLS. However, the fact that it is available 2 days earlier makes it a potentially useful input in any effort to track the economy in real time; it offers a nice illustration of the trade-off between accuracy and timeliness that we discuss above.

Given the richness of the available macroeconomic information, what might be the role for the ever-growing alternative sources of big data, such as Internet search queries, electronic payments, or online prices, in monitoring the economy? Choi & Varian (2012) and Askitas (2015) highlight the potential of such data in predicting current economic activity. They show that Google Trends data can improve the forecasting of timely economic indicators, such as automobile sales and initial claims, when compared to a univariate autoregressive model. However, Li (2016) and Gil et al. (2017) show that Google search queries and other alternative data have limited marginal information content once one takes into account the range of economic data already available, such as that shown in **Table 2**.

Moreover, these alternative sources of information are also subject to a trade-off between timeliness and quality. Although they have the potential to allow monitoring of the economy closer to real time, since they do not need to be processed by statistical agencies, this is also a shortcoming. Indeed, Li (2016) and Lazer et al. (2014) caution about measurement problems that have not yet been fully addressed for these new data sources. By contrast, most economic indicators are processed to eliminate problems such as bias, nonrepresentativeness, and seasonality: These adjustments take time, which is why official statistics are not quite as timely.[7]

Nevertheless, there are cases in which alternative data can prove very useful. The Billion Prices Project (Cavallo & Rigobon 2016) is a good example of the successful use of this type of big data in the absence of accurate information from official statistical agencies. At its inception, the project collected daily prices from large online retailers in Argentina and was able to provide reliable and timely measures of inflation at a time when the official numbers were being manipulated for political reasons. Alternative sources of big data could also be useful to monitor aspects of the economy that are less covered by official statistics, such as the service sector and sectors in the digital economy that are not yet well captured in the national accounts (Nakamura et al. 2017). Finally, this type of big data can be useful to monitor very local economic developments in a timely manner. For example, Aladangady et al. (2016) use electronic transactions data to analyze the effect of hurricanes on consumption in the areas directly affected.

For the purpose of nowcasting the US economy, in this review, we currently restrict ourselves to the use of traditional macroeconomic releases. These sources of information have been developed and used reliably over the past century, thanks to their careful measurement and well-understood connection with economic activity. The promise of alternative sources of big data in monitoring economic activity in real time is exciting. However, given the richness and reliability of traditional economic indicators, the contribution from these new data sources currently appears to be minimal.

Table 2 provides a qualitative snapshot of the richness and complexity of the regularly available data that are tracked by economists and other observers and that are accordingly used as an input in the Federal Reserve Bank of New York model. **Figure 2** provides a complementary, more quantitative perspective on these same data by plotting their joint evolution over time. The heat map on the horizontal plane highlights the degree of comovement in the series, with more intense red denoting realizations further below the mean and brighter yellow denoting realizations further above the mean. The red ridges in the early 1990s, early 2000s, and, most notably, 2008 and 2009 emphasize quite clearly the three recessions in the sample. This visualization captures in a simple, unstructured way not only the comovement that drives the data flow over the business cycle, but also the extent to which idiosyncratic factors drive each series in different directions at any given point in time. Nowcasting is essentially a structured, formal, and efficient way of extracting the business cycle signal and discarding the idiosyncratic noise from this rich and complex set of data. Section 4 introduces the econometric theory behind this exercise, while Section 5 presents more details on how these ideas are implemented in the New York Fed Staff Nowcast.

4. DEALING WITH BIG DATA: ECONOMETRIC MODELS

As discussed extensively in the previous sections, monitoring macroeconomic conditions in real time is inherently a big data problem. It crucially relies on the availability and the exploitation of a large amount of complex data. Increasing the complexity of the data leads to increasing complexity in the models, with a growing number of parameters to estimate. Indeed, dealing with large data sets using overly simplified models may lead to misspecification, since important features are omitted. However, modeling the interactions among a large number of variables leads to a proliferation of parameters, which implies large estimation uncertainty, which in turn makes the results from traditional tools unreliable and unstable. This fact is often referred to as the

[7]As an example, in 2017, the UK Office of National Statistics announced that, starting in 2018, it will postpone by 2 weeks the release of the first estimate of GDP because of large errors in the recent period (Off. Natl. Stat. 2017).

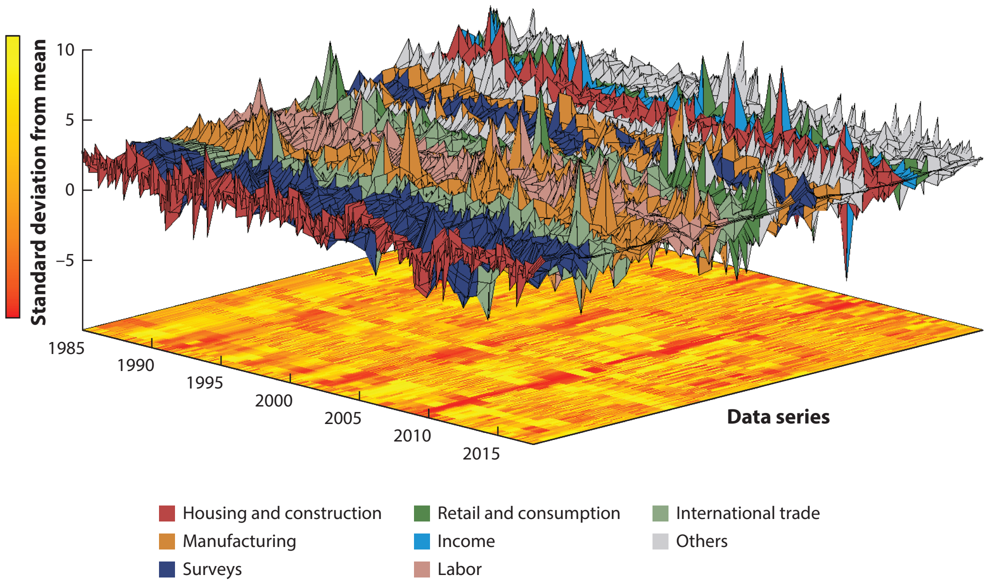


Figure 2

Big data in macroeconomics. The three-dimensional surface plot displays the standardized time series for the economic indicators used in the Federal Reserve Bank of New York nowcasting model, colored by category, as indicated in the legend. The heat map on the horizontal plane shows observations above (*yellow*) and below (*red*) the mean; the intensity of the color is a function of the size of the deviation. Figure created using the authors' calculations based on data from Haver Analytics.

curse of dimensionality: The modeler faces a trade-off between excessive simplicity (leading to misspecification) and excessive complexity (leading to instabilities). The econometrics of big data aims to turn the curse of dimensionality into a blessing by capturing in a parsimonious manner the salient features of the interactions among many series.

From an econometric perspective, estimation is challenging whenever the number of parameters is large relative to the number of observations. This is known in statistics as the large p, small n paradigm, where p stands for the number of variables and n indicates the number of observations. Given their long tradition in handling a large amount of heterogeneous and complex data with a short time span, it is not surprising that macroeconomists have pioneered the statistical analysis of big data. At the root of the recent statistical developments is the key insight of Burns & Mitchell (1946) that we discuss above: The pervasiveness of common fluctuations across different sectors of the economy implies strong cross-sectional correlations, suggesting that the bulk of fluctuations is essentially driven by a few common sources. Dynamic factor models (DFMs) build on this basic fact to provide a parsimonious and yet suitable representation for the macroeconomic series; they are one of the main tools that macroeconomists currently use to handle big data.

A DFM assumes that many observed variables $(y_{1,t}, \ldots, y_{n,t})$ are driven by a few unobserved dynamic factors $(f_{1,t}, \ldots, f_{r,t})$, while the features that are specific to individual series, such as measurement errors, are captured by idiosyncratic errors $(e_{1,t}, \ldots, e_{n,t})$. The empirical model can be summarized in the following equation:

$$y_{i,t} = \mu_i + \lambda_{i,1} f_{1,t} + \cdots + \lambda_{i,r} f_{r,t} + e_{i,t}, \text{ for } i = 1, \ldots, n, \qquad 1.$$

which relates the data $y_{i,t}$ to the r latent common factors $f_{1,t}, \ldots, f_{r,t}$ through the factor loadings $\lambda_{i,1}, \ldots, \lambda_{i,r}$. The idiosyncratic component $e_{i,t}$ captures the movements specific to each variable i.

As discussed in Section 2, factor models have a long tradition in the statistical and econometric literature. However, the application to big data is relatively recent. The earliest contributions are those of Forni et al. (2000) and Stock & Watson (2002a,b), who introduce principal components estimators for large DFMs in economics. Also associated with these developments are the earliest occurrences of the term big data in the academic context [for an interesting discussion of the origin(s) of the term big data, see Diebold 2012]. West (2003) pioneers Bayesian inference with large factor models in statistics and introduces the large p, small n paradigm, which translates into large n, small T in our context, where T is the sample size. These pioneering papers have led to many further advances in this research field; these advances have recently been surveyed by Stock & Watson (2016).

As initially pointed out by Giannone et al. (2008), DFMs are particularly suitable for nowcasting and monitoring macroeconomic conditions in real time. This is because these models are naturally cast in a state-space form, and thus, inferences can be drawn using Kalman filtering techniques, which in turn provide a convenient and natural framework for handling the irregularities of the data in real time (i.e., mixed frequencies and nonsynchronicity of the data releases) and updating the predictions. Indeed, the Kalman filter digests incoming data in a coherent and intuitive way: It updates the predictions of the model recursively by weighting the innovation components of incoming data on the basis of their timeliness and their quality. Moreover, as the model produces forecasts for all variables simultaneously, the analysis of the flow of data does not require piecing together many separate, unrelated models.

To illustrate the versatility of the DFM framework, consider how it handles mixed-frequency data. The idea is to write the state-space system at the highest available data frequency (or even higher) and treat the lower-frequency data as a filtered version of latent high-frequency data that are periodically missing. In our case, the highest frequency is monthly, and the lowest frequency is quarterly; thus, for instance, the quarterly growth rate of GDP can be reconstructed through a filter applied to a latent monthly growth rate (for the computation details of this frequency aggregation, see Mariano & Murasawa 2003). The same idea can be easily applied to higher-frequency data; for example, Bańbura et al. (2013) mix daily, weekly, monthly, and quarterly frequencies. Until recently, however, the literature resorted to approximations to this idea based on regression models owing to computational constraints and the lack of a complete understanding of the properties of large-dimensional models estimated with Kalman filtering techniques. Examples of these approximations are ridge regressions (Golinelli & Parigi 2007, Parigi & Schlitzer 1995), MIDAS models (Andreou et al. 2013, Ghysels et al. 2007), simple dimension reduction techniques such as principal components (Marcellino & Schumacher 2010), or averaging of many small models (Kitchen & Monaco 2003).

Heuristic solutions to handling the nonsynchronicity of data releases essentially consist of artificially shifting and realigning the data set at every update. The drawback of these approaches is that they make it difficult to interpret why and how incoming data affect the predictions. The reason for this is that these models only predict a single target variable, without a model for the predictors. In the absence of a prediction for each series, they do not allow the computation of the news component of each release, which in turn is the key to the clear interpretation of the impact of new data releases. In addition, because of realignments and other approximations, the partial model changes at every update, and the meaning of the parameters also changes. In contrast, by jointly modeling all variables, our approach enforces internal consistency and allows one to interpret the impact of incoming releases in terms of news. The nonsynchronicity of the data does not affect the model because the Kalman filter handles all possible features of the data available within the same invariant model. This is a desirable feature because the model depends only on the properties of the data and not on how and when they are released.

To conduct inference in DFMs using likelihood-based methods and Kalman filtering techniques, one models the common factors and the idiosyncratic components as Gaussian autoregressive processes, which accounts for their serial correlation and persistence:

$$f_{j,t} = a_j f_{j,t-1} + u_{j,t}, \quad u_{j,t} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \sigma^2_{u_j}\right) \quad \text{for } j = 1, \ldots, r, \tag{2.}$$

$$e_{i,t} = \rho_i e_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \sigma^2_{\varepsilon_i}\right) \quad \text{for } i = 1, \ldots, n. \tag{3.}$$

Equations 1–3 form a state-space model where the common factors and the idiosyncratic components are unobserved states. Equation 1 is known as the measurement equation and links the data to the unobserved states. Equations 2 and 3, known as the transition equations, describe the dynamics of the system. To avoid the proliferation of parameters, it is typical to maintain a parsimonious empirical specification for the idiosyncratic components and assume that they are cross-sectionally orthogonal.

A model of this kind was first used by Stock & Watson (1989) to extract a single common factor ($r = 1$) from a small set of monthly core indicators, including employment, industrial production, sales, and income ($n = 4$). Mariano & Murasawa (2003) extend the model to include GDP growth ($n = 5$), and Aruoba et al. (2009) extend it to include weekly unemployment claims ($n = 6$). This framework also encompasses simpler approaches to the construction of business cycle indexes. In particular, the extracted common factor corresponds to the principal components if the empirical model is constrained to be static, i.e., assuming serially uncorrelated factors ($a_1 = \cdots = a_r = 0$) and idiosyncratic components ($\rho_1 = \cdots = \rho_n = 0$), and with homogeneous signal-to-noise ratio ($\sigma^2_{\varepsilon_1} = \cdots = \sigma^2_{\varepsilon_n}$). If there is only one factor ($r = 1$) loaded homogeneously by all variables ($\lambda_{1,1} = \cdots = \lambda_{n,1}$), then the extracted common factor corresponds to cross-sectional averages.

The use of likelihood-based methods for factor models with big data is advocated by Doz et al. (2012), who establish the viability of the approach. They show that, if the factor structure is strong, then maximum likelihood estimates are not only consistent when the sample size T and the cross-sectional dimension n are large, but also robust to cross-sectional misspecification, time-series correlation of the idiosyncratic components, and non-Gaussianity. In this respect, the method is a quasi–maximum likelihood estimator in the sense of White (1982). Importantly, no constraint is required on the number of series n that can be handled for a given sample size T, which ensures that the approach is suitable for the large n, small T paradigm.

In practice, the estimates can be conveniently computed iteratively using the Kalman smoother and the expectation–maximization (EM) algorithm. The algorithm is initialized by computing principal components, and the model parameters are estimated by ordinary least squares (OLS) regression, treating the principal components as if they were the true common factors. This is a good initialization, especially with a large data set, given that principal components are reliable estimates of the common factors. In the second step, given the estimated parameters, an updated estimate of the common factors is obtained using the Kalman smoother. Stopping at the second step gives the two-step estimate of the common factors used by Giannone et al. (2008) and studied by Doz et al. (2011). Maximum likelihood estimation is obtained by iterating the two steps until convergence, taking into account at each step the uncertainty related to the fact that factors are estimated.[8]

The model described above is the one used for the New York Fed Staff Nowcast, which we illustrate in Section 5. We keep it as simple as possible to minimize pretesting and specification

[8]For details on the EM algorithm for the estimation of large factor models, the reader is referred to Doz et al. (2012). Bańbura & Modugno (2014) show how to perform the parameter estimation step in the presence of arbitrary patterns of missing data.

choices, but it can be easily extended to include more lags in the autoregressive process and allow for dynamic interactions among common factors. Other extensions can be useful to further improve accuracy. D'Agostino et al. (2016) extend the model to accommodate heterogeneity in the lead-lag relationships of different indicators along the business cycles, Kim & Nelson (2001) introduce time-varying parameters in the form of Markow switching, Antolin-Diaz et al. (2017) introduce time variation in the intercept, and Marcellino et al. (2016) introduce time-varying volatility. It is worth emphasizing that in spite of, and indeed thanks to, its simplicity, this basic model has been successfully applied to nowcasting in many economies with very different characteristics. These include large developed economies and small open economies, as well as emerging market and developing economies.[9]

In this review, we focus mainly on factor models, since they summarize the state of the economy in a lower dimension and thus provide a direct link to business cycle analysis.[10] However, as pointed out in Section 2, VAR models offer an alternative approach to monitoring the economy in real time, since they share many of the advantages of the DFM. They also provide a joint model of all variables, are internally coherent, and can be cast in a state-space form, allowing the economist to handle missing data via filtering techniques and update forecasts with each new data release.

Applications of VAR models with mixed-frequency data include those of Zadrozny (1990) and Mittnik & Zadrozny (2005). A systematic treatment of the models is provided by Anderson et al. (2016a,b). Until recently, these models were not used for nowcasting, since they are richly parameterized and thus can only handle a small number of data series.[11] Recent research has shown, however, that Bayesian shrinkage makes VAR models suitable for high-dimensional problems (see Bańbura et al. 2010, Giannone et al. 2015, Koop 2012). The basic idea consists of addressing the curse of dimensionality by using a parsimonious naive prior to discipline the estimation of a very flexible, densely parameterized, and complex model. This is an important line of research, since Bayesian inference provides a coherent probabilistic framework that can be exploited to greatly reduce the number and importance of subjective choices, such as data transformations or selection of the priors (see Carriero et al. 2015, Giannone et al. 2015). Recent applications of mixed frequency BVARs to nowcasting with big data include those of Brave et al. (2016) and McCracken et al. (2015) (for recent surveys of BVAR models, see Karlsson 2013, Koop 2017).

5. NOWCASTING IN PRACTICE

In this section, we describe the platform used at the Federal Reserve Bank of New York to track US real GDP growth.[12]

[9]For instance, descriptions of nowcasting are given by Giannone et al. (2008), Bańbura et al. (2013), Lahiri & Monokroussos (2013), and Liebermann (2014) for the United States; Angelini et al. (2011) and Bańbura et al. (2011) for the aggregate euro area economy, as well as Runstler et al. (2009) for individual member countries; Bragoli (2017) for Japan; Chernis & Sekkel (2017) for Canada; Aastveit & Trovik (2012) and Luciani & Ricci (2014) for Norway; Matheson (2010) for New Zealand; Anesti et al. (2017) for the United Kingdom; Dahlhaus et al. (2017) for the BRIC (Brazil, Russia, India, and China) countries and Mexico; Bragoli et al. (2015) for Brazil; Bragoli & Fosten (2017) for India; Yiu & Chow (2010) for China; Caruso (2015) for Mexico; Luciani et al. (2015) for Indonesia; and Kabundi et al. (2016) for South Africa. For an extensive survey, the reader is referred to Bańbura et al. (2011, 2013) and Luciani (2017).

[10]Giannone et al. (2010, 2016) perform the same analysis with a linearized dynamic stochastic general equilibrium model. This is straightforward, since the model has a state-space form.

[11]For example, Giannone et al. (2009) apply this type of model to nowcasting euro area GDP with a handful of monthly indicators.

[12]A similar platform, called GDPNow, is used at the Federal Reserve Bank of Atlanta for nowcasting US GDP growth (Higgins 2014). That model also builds on the work of Giannone et al. (2008); however, it combines forecasts of the components of

The New York Fed Staff Nowcast is based on the dynamic factor model described in Section 4 and incorporates all the releases listed in **Table 2**. As described in Section 3, these are the releases most widely followed by market participants. While the nowcasting model is parsimonious and can accommodate many data series, it includes only the headlines of each release, those that move markets and make front-page news. The model does not include disaggregated data, since there are no substantial gains in prediction from including them, although they can be useful for interpretation (for a detailed discussion, see Bańbura et al. 2011, 2013). Therefore, for example, from the Employment Situation Report, the model incorporates the unemployment rate and nonfarm payrolls but does not include information on employment by age or industry; similarly, the model includes only total indexes for industrial production and capacity utilization, disregarding sectoral disaggregation. We should note that financial variables are not included in the model: Although they provide timely information, they tend to be quite volatile and have a limited role in nowcasting GDP growth once a rich set of macroeconomic variables has been included (see Bańbura et al. 2013, Knotek & Zaman 2017). However, going beyond the prediction of the central tendency, financial conditions can provide valuable information, especially for monitoring downside risks (Adrian et al. 2016).

All variables are listed in the first column of **Table 3**. The colored box next to the series' name indicates the category to which the series is assigned. Each series enters the model in stationary form: In most cases, this requires simply including the series as it is tracked by financial market participants (i.e., as reported in Bloomberg).[13] The last column of **Table 3** indicates the units in which each series enters the model.

We specify the model by assuming that a single common factor, the global factor, affects all variables.[14] In addition, we include a few local blocks to control for idiosyncrasies in particular subgroups of series; this can improve inference even though estimation is robust to the presence of local correlations among idiosyncratic components. Specifically, to model the local correlations in survey data, we include the soft block, on which only variables representing economic agents' perceptions and sentiments load. Two additional local blocks are included for real and for labor variables; the structure of factor loadings is given in the second column of **Table 3**.

Figure 3 reports the standardized data, along with the global factor, estimated from the model specification of **Table 3**. It is clear that the common (global) factor captures the bulk of the covariation between the variables.

The New York Fed Staff Nowcast is updated daily at 10:00 a.m. whenever new data releases are issued. This daily updating allows users to read the real-time data flow and quantify how each data release contributes to updates in the forecasts of all other variables. The factors, and thus the nowcast, change if either the data change or the model parameters are reestimated. The data change constantly, not only because new data are released, but also because data are revised. Model parameters are reestimated at the beginning of every quarter using the most recent 15 years of data. In the nowcast detail table, parameter revisions are changes to the nowcast due to the reestimation, while data revisions reflect changes in previously released data; both are classified within the "Others" category.

GDP with an accounting step that mimics the key elements of the GDP construction process followed by the BEA, as discussed in Section 3. Partly as a result of this modeling choice, GDPNow is especially focused on predicting the advance estimate of GDP growth.

[13]There are a few exceptions, however. Housing starts, for instance, are typically tracked in levels by market participants, but because of evident trends, this series enters the model in monthly changes.

[14]While, in general, the single factor model has been proven quite robust, it is possible to use selection criteria and tests to select the number of factors. For a discussion of these methods in the context of large n, large T, the reader is referred to Stock & Watson (2016). For an extension of these criteria in the context of quasi–maximum likelihood estimators of large DFMs, the reader is referred to Coroneo et al. (2016).

Table 3 Data series that enter the New York Fed Staff Nowcast

Data series (category)	Factor loadings[a]				Units
	G	S	R	L	
All employees: total nonfarm (labor)	X			X	Level change (thousands)
Real GDP (other)	X		X		QoQ % change (annual rate)
ISM mfg.: PMI composite index (surveys)	X	X			Index
CPI-U: all items (other)	X				MoM % change
Manufacturers new orders: durable goods (manufacturing)	X		X		MoM % change
Retail sales and food services (retail and consumption)	X		X		MoM % change
New single family houses sold (housing and construction)	X		X		MoM % change
Housing starts (housing and construction)	X		X		MoM % change
Civilian unemployment rate (labor)	X			X	Ppt. change
Industrial production index (manufacturing)	X		X		MoM % change
PPI: final demand (other)	X				MoM % change
ADP nonfarm private payroll employment (labor)	X			X	Level change (thousands)
Empire State Mfg. Survey: general business conditions (surveys)	X	X			Index
Merchant wholesalers: inventories: total (manufacturing)	X		X		MoM % change
Value of construction put in place (housing and construction)	X		X		MoM % change
Philly Fed Mfg. business outlook: current activity (surveys)	X	X			Index
Import price index (international trade)	X				MoM % change
ISM nonmanufacturing: NMI composite index (surveys)	X	X			Index
ISM mfg.: prices index (surveys)	X	X			Index
Building permits (housing and construction)	X		X		Level change (thousands)
Capacity utilization (manufacturing)	X		X		Ppt. change
PCE less food and energy: chain price index (other)	X				MoM % change
CPI-U: all items less food and energy (other)	X				MoM % change
Inventories: total business (manufacturing)	X		X		MoM % change
Nonfarm business sector: unit labor cost (labor)	X			X	QoQ % change (annual rate)
JOLTS: job openings: total (labor)	X			X	Level change (thousands)
Real personal consumption expenditures (retail and consumption)	X		X		MoM % change
PCE: chain price index (other)	X				MoM % change
ISM mfg.: employment index (surveys)	X	X			Index
Export price index (international trade)	X				MoM % change
Manufacturers shipments: durable goods (manufacturing)	X		X		MoM % change
Mfrs. unfilled orders: all manufacturing industries (manufacturing)	X		X		MoM % change
Manufacturers inventories: durable goods (manufacturing)	X		X		MoM % change
Real gross domestic income (other)	X		X		QoQ % change (annual rate)
Real disposable personal income (income)	X		X		MoM % change
Exports: goods and services (international trade)	X		X		MoM % change
Imports: goods and services (international trade)	X		X		MoM % change

[a]G, S, R, and L indicate the global, soft, real, and labor factors, respectively.

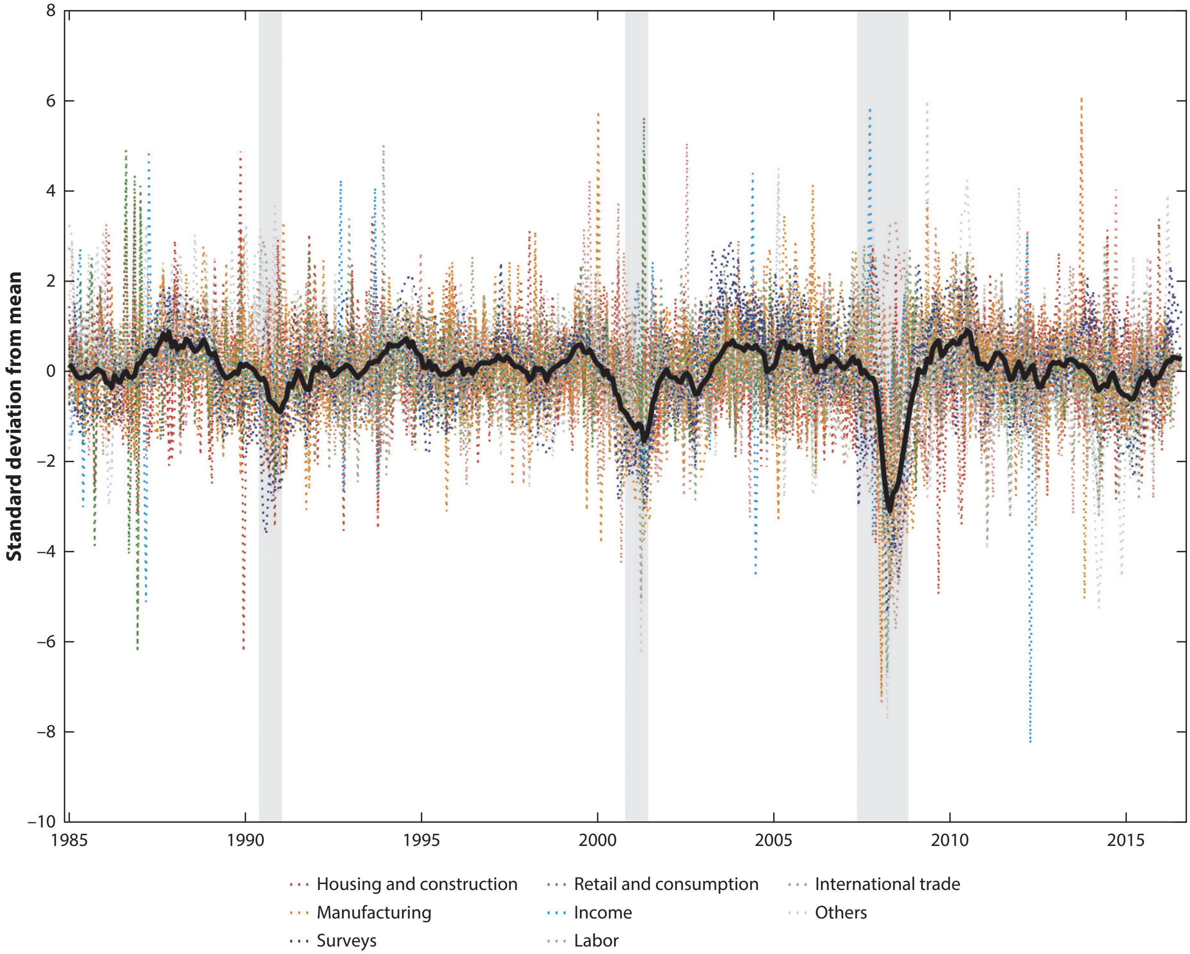
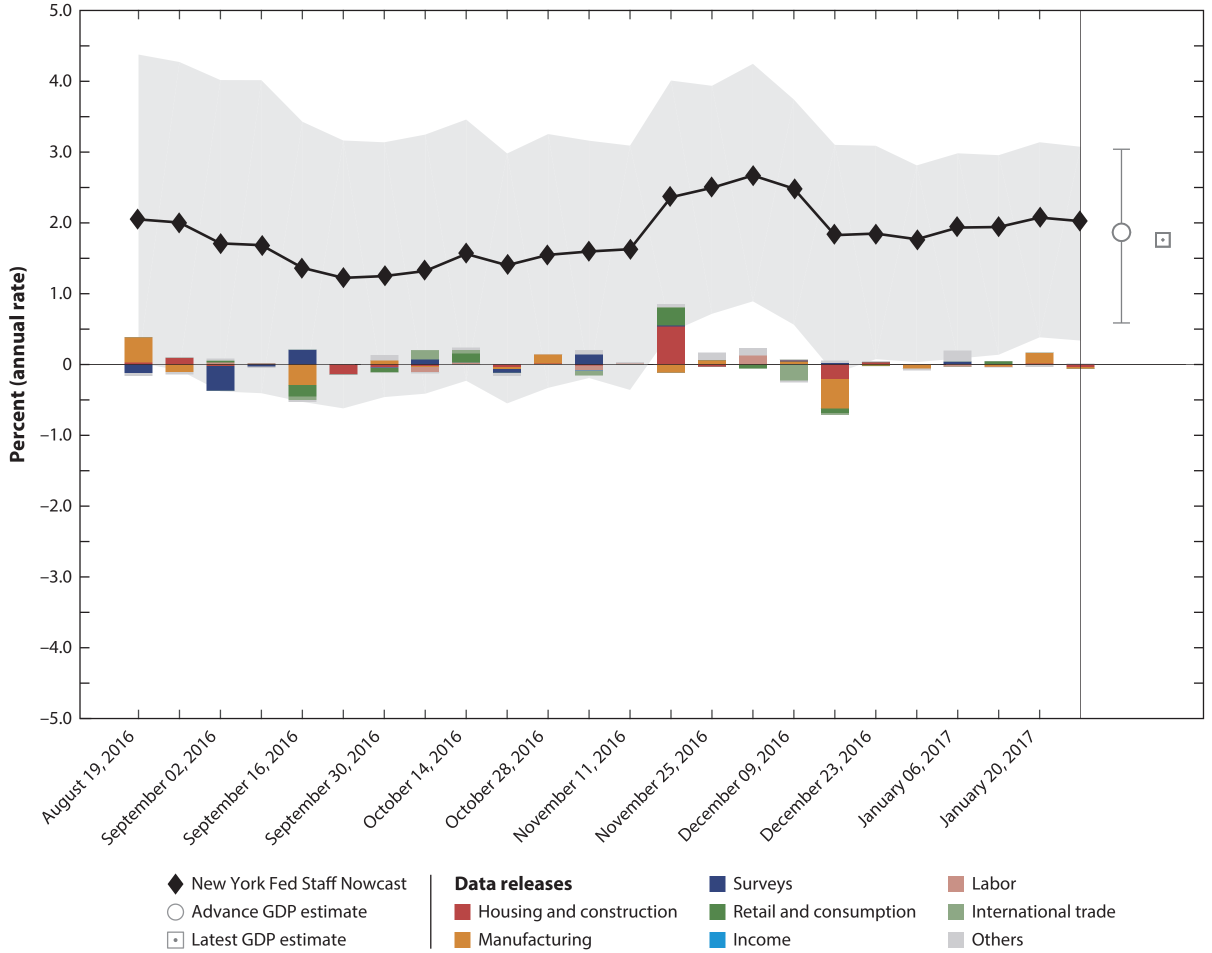


Figure 3

Estimated global factor. The dotted lines represent all the data series that enter the Federal Reserve Bank of New York nowcasting model, in standard deviations from their mean and colored by category, as indicated in the legend. The solid black line is the global factor estimated from the dynamic factor model. Shaded areas indicate National Bureau of Economic Research (NBER) recessions. Figure created using authors' calculations based on data from Haver Analytics.

Figure 4 reports the evolution of the nowcast of real GDP growth in 2016:Q4. This figure is the same as **Figure 1**, but with added shading to provide information about forecasting uncertainty. In particular, the shaded area represents the 68% probability interval constructed using the empirical distribution of the forecast errors. We discuss forecasting performance in more detail below, but it should be noted that the bands narrow as the quarter progresses and information accumulates. This suggests that the data contain useful information that the model is able to exploit in real time. Notice, too, the substantial uncertainty also present in the official release of GDP, as illustrated in **Figure 4** by the error bar around the release, which reflects data revisions. This uncertainty is similar in magnitude to that of the previous model forecast, suggesting that the model predictions are roughly as accurate as the first release in predicting the latest available estimates of GDP growth.



Update	Release	Data series	Reference period	Units	Forecast	Actual	Weight	Impact	Nowcast GDP growth
					[*a*]	[*b*]	[*c*]	[*c*(*b* − *a*)]	
Sep09									1.69
	8:30AM Sep14	Import price index	Aug	MoM % change	−0.119	−0.248	0.029	−0.004	
	8:30AM Sep14	Export price index	Aug	MoM % change	0.058	−0.826	0.053	−0.047	
	8:30AM Sep15	Retail sales and food services	Aug	MoM % change	0.489	−0.295	0.206	−0.161	
	8:30AM Sep15	PPI: Final demand	Aug	MoM % change	−0.021	0.000	0.040	0.001	
	8:30AM Sep15	Empire State Mfg. Survey: General business conditions	Sep	Index	−0.583	−1.99	0.014	−0.019	
	8:30AM Sep15	Philly Fed Mfg. business outlook: current activity	Sep	Index	−1.50	12.8	0.016	0.228	
	9:20AM Sep15	Industrial production index	Aug	MoM % change	−0.051	−0.433	0.415	−0.158	
	9:20AM Sep15	Capacity utilization	Aug	Ppt. change	−0.100	−0.357	0.520	−0.134	
	8:30AM Sep16	CPI-U: all items	Aug	MoM % change	0.048	0.199	0.062	0.009	
	8:30AM Sep16	CPI-U: all items less food and energy	Aug	MoM % change	0.142	0.252	0.021	0.002	
		Data revisions						−0.037	
Sep16									1.37

(*Caption appears on following page*)

Figure 4 (*Figure appears on preceding page*)

The New York Fed Staff Nowcast for 2016:Q4. The solid black line is the progression of the nowcast of real GDP growth throughout the period of updates, which begins 1 month before the reference quarter and comprises the 3 months during and 1 month after the reference quarter, until the Bureau of Economic Analysis publishes the advance GDP release; after this release, the nowcast for that quarter is no longer updated. Each black diamond on the line is the nowcast for the particular week indicated on the x axis; the colored bar corresponding to that diamond represents the contribution of the surprises in the releases of that week to the change in the nowcast. Each bar potentially has many segments of different colors, which represent the net contributions of different categories of data. The circle and square at the right of the chart are the first and latest official GDP estimates, respectively. Details on the impact of each data release over the course of the week of September 12–16 are reported in the table below the legend. For each series, the table reports the day and time of the release (*second column*) and the reference period (*fourth column*), as well as the units in which the series is reported (*fifth column*). In the next four columns, the table reports, respectively, the model prediction for the series [a], the actual value of the series in the release [b], the weight [c] that the model assigns to the surprise (or news) [$(b-a)$] in the nowcast of GDP growth, and the impact [$c(b-a)$], i.e., how this surprise changes the nowcast. The gray shading around the nowcast progression represents the interval between the 16th and 84th percentiles of the empirical distribution of the forecast errors; the whisker around the circle represents the same 68% probability interval of historical revision errors from the first estimate of GDP to the latest. Both intervals are based on real-time prediction errors over the 2000–2016 sample (see **Figure 5**). Figure created using Federal Reserve Bank of New York, Nowcasting Report (**https://www.newyorkfed.org/research/policy/nowcast**) with additional calculations from the authors.

Figure 4 shows that the initial model prediction for 2016:Q4 GDP growth on August 19, 2016, was approximately 2.0%. After an initial fall to a low of 1.2%, due largely to negative surprises from survey, manufacturing, and retail and consumption data, the nowcast steadily increased until, in the middle of the quarter, in the week of November 18, it jumped up almost one full percentage point to 2.6% due to positive surprises from housing data and retail and consumption data. This increase was partially reverted just a few weeks later, on December 16, due to negative news from manufacturing and housing data. The nowcast moved slightly upward in the following 6 weeks and was last recorded at 2.0% on January 27, 2017, just before the advance GDP release. By comparison, the BEA advance estimate of real GDP growth was 1.9% (circle in **Figure 4**), and the latest official estimate was 2.1% (square).

We performed a comprehensive backtesting to evaluate the real-time performance of the model by computing the nowcast recursively on real-time vintages of data reconstructed to replicate the data exactly as they were available at the time. The nowcast for any given week is therefore precisely what would have been computed by a forecaster running the model at that time. Backtesting was conducted over the period from January 2000 through January 2017. The incoming data were automatically incorporated at the end of any given week. As we do currently, we estimated the parameters recursively at the beginning of every quarter.

Figure 5 reports the errors of the real-time nowcast, relative to the most recent GDP data, for all quarters in the evaluation sample. For comparison, we also report in the figure the errors of the SPF forecast for real GDP growth in the current quarter and the revision error of the advance GDP release. Considering the universe of the nowcast errors, we uncover a preponderance of negative errors, i.e., an upward bias in the nowcast. This pattern is related to the much-discussed issue of residual seasonality in first-quarter real GDP growth.[15] We therefore partition the error distribution into first-quarter errors and errors for all quarters except first quarters. We report the interval between the 16th and 84th percentiles separately for these partitions. These are the bands superimposed on the nowcast progression plot to provide a measure of forecast uncertainty. Similarly, we report 68% probability intervals for the revision errors of advance GDP and the prediction errors of the median SPF forecast separately for first quarters and for all other quarters.

[15]Moulton & Cowan (2016) report the BEA's findings on residual seasonality and its plan to publish a not–seasonally adjusted GDP series (see also Barigozzi & Luciani 2018, Gilbert et al. 2015, Groen & Russo 2015, Kliesen 2017, Lunsford 2017, Phillips & Wang 2016, Rudebusch et al. 2015, Stark 2015).

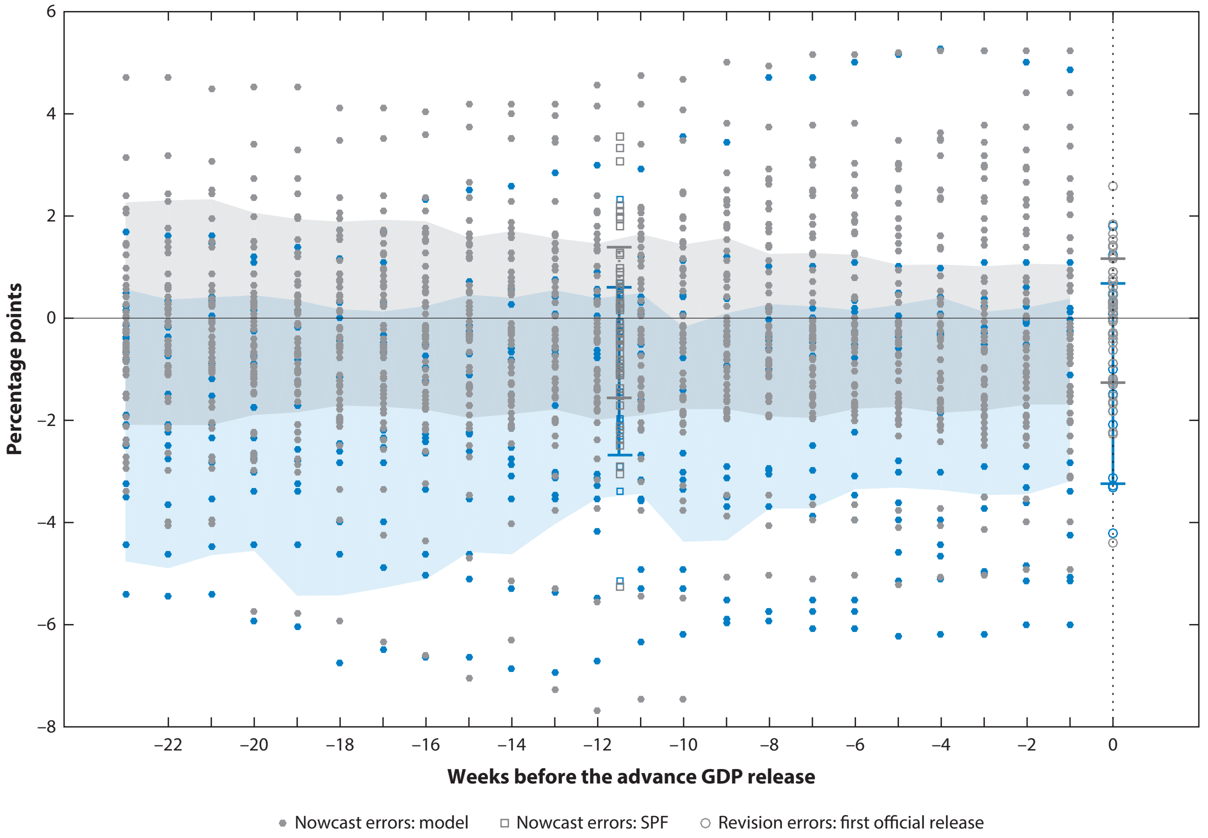


Figure 5

Empirical nowcast error distribution. Nowcast errors are computed as the difference between the real-time nowcast and the latest official GDP estimate. The *x* axis indicates the point in the quarter when the nowcasts were made, measured in terms of weeks before the first official GDP release. The dots are the model nowcast errors for individual quarters over the evaluation sample 2000–2016. Errors are partitioned in two groups: Blue represents errors for first quarters, and gray represents errors for all other quarters. Shaded areas represent the interval between the 16th and 84th percentiles of the empirical distribution of the forecast errors in the respective partitions. The squares in the middle of the quarter represent the nowcast errors for the median of Survey of Professional Forecasters projections. The circles at the end of the quarter are the revision errors for the first GDP release. The overlapping whiskers on top of the circles and squares represent the 68% probability intervals based on their empirical distribution. Figure created using the authors' calculations.

Inspecting the shaded bands reveals that much of the upward bias comes from first-quarter nowcasts, in line with the issue of residual seasonality discussed above. The asymmetry is evident not only in the nowcasts but also in the revision errors of advance GDP estimates, as well as the median SPF forecast errors. **Figure 6** shows the progression of the GDP nowcast for 2017:Q1, where the shaded area represents the 68% probability interval constructed using the empirical error distribution for nowcasts of GDP in the first quarter. The shading gives a sense of the magnitude of the uncertainty surrounding first-quarter nowcasts relative to those of other quarters.

Beyond issues pertaining to residual seasonality, the error distributions clearly show the attributes of a good forecast. Contrary to the first quarters, in which the errors exhibit significant downward bias, the errors for the other quarters are generally distributed symmetrically around zero. Furthermore, the bands get narrower as time goes on, indicating, on average, a more accurate prediction of GDP growth over the nowcasting period as more information about the economy

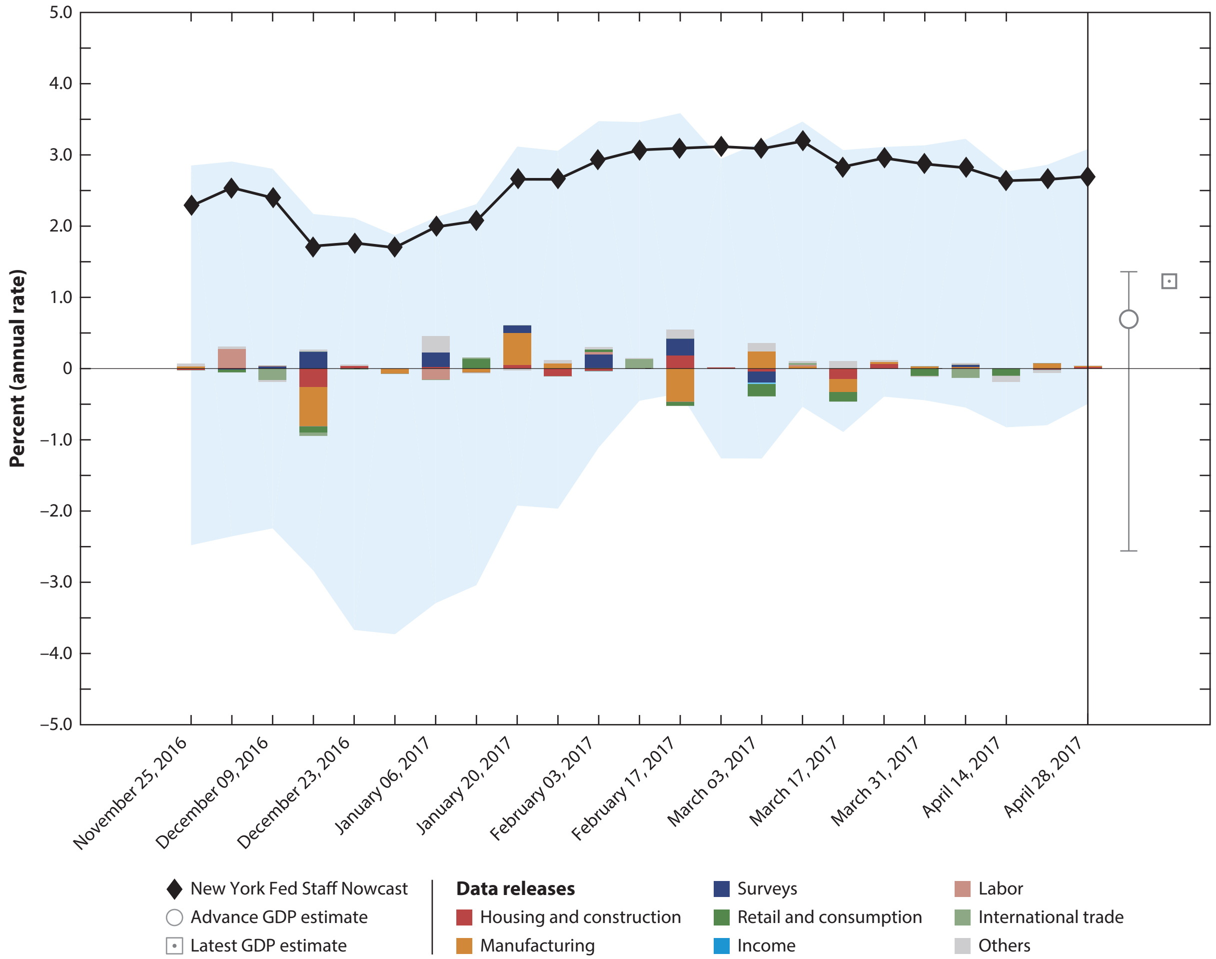


Figure 6

The New York Fed Staff Nowcast for 2017:Q1. The solid black line is the progression of the nowcast of real GDP growth for 2017:Q1. The circle and square at the right of the chart are the first and latest official GDP estimates, respectively. Colored bars represent the contributions of data releases over the course of each week to changes in the nowcast, grouped by categories, as indicated in the legend. The blue shading around the nowcast progression represents the interval between the 16th and 84th percentiles of the empirical distribution of the forecast errors. The circle and square at the right of the chart are the first and latest official GDP estimates, respectively. The whisker around the circle represents the same 68% probability interval of historical revision errors from the first estimate of GDP to the latest. Both intervals are based on real-time prediction errors over the 2000–2016 sample (see **Figure 5**). Figure created using the Federal Reserve Bank of New York, Nowcasting Report (**https://www.newyorkfed.org/research/policy/nowcast**) with additional calculations from the authors.

is released. Finally, at the end of the nowcast updating period, the bands are similar to the error bars for the advance GDP release, indicating that the uncertainty surrounding the final nowcast made for each quarter is similar to that of the BEA's first estimate in predicting the true value of aggregate output growth in the economy. Moreover, the error bars for the SPF align closely with, but lie within, the nowcast error bands at the same horizon, indicating that professional forecasters are slightly more accurate than the nowcasting model. Model accuracy tends to improve as time progresses and is in line with that of the SPF benchmark near the end of the reference quarter.

We conclude this analysis by asking: What are the most important variables driving the nowcast, when, and why? **Figure 7** reports the average (absolute) weekly impact of each series, grouped by category, computed in real time over the evaluation sample 2000–2016. From this figure, three features are evident. First, the most prominent colors are blue, green, orange, and red, indicating that survey, consumption, manufacturing, and housing data are the main contributors to changes in the nowcast. Second, the bell shape of the plot indicates that the most useful information for the nowcast arrives in the middle of the nowcasting period, when data for the reference period first become available. Conversely, surprises move the nowcast less both at the beginning and at the end of the period: at the beginning because, at that time, signals for GDP growth are still too weak and at the end because, by then, most useful information has become available and there is little room for improvement. Third, we see from the contribution of surveys that soft data have a large

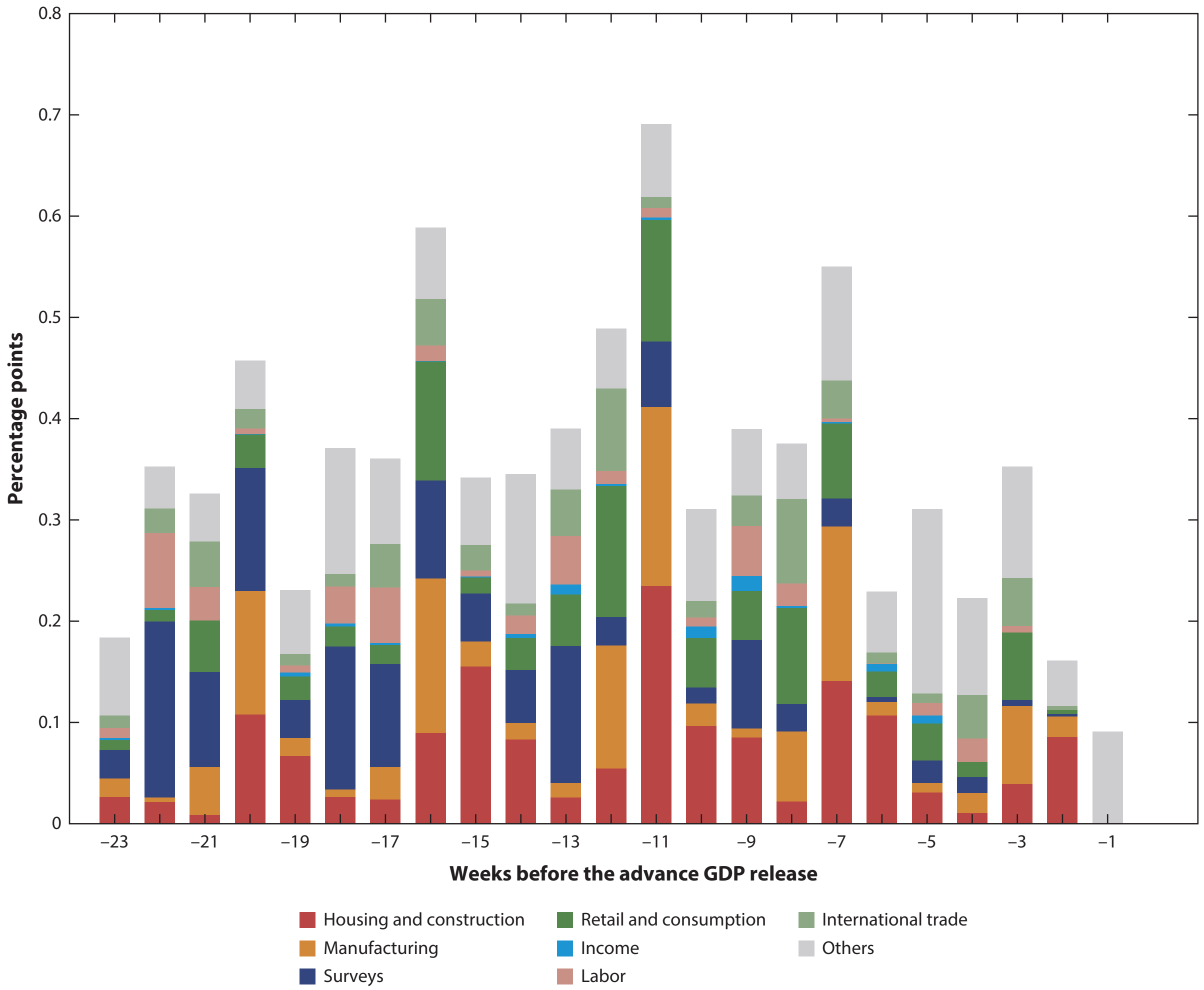


Figure 7

Impact of data releases on the nowcast. The bars indicate the average absolute impact of each data series on the nowcast computed in real time over the evaluation sample 2000–2016. The series are grouped by category, as indicated in the legend. The *x* axis indicates the point in the quarter when the nowcasts were made, measured in terms of weeks before the first official GDP release. Figure created using the authors' calculations.

impact at the beginning of each nowcasting time frame. Later, as more information accumulates, their impact diminishes, and hard data become more important. This confirms that timeliness is just as important as the quality of the data.

Overall, each of the series tracked by the nowcast provides relevant information at various updating horizons. The combined information allows us to track the economy during each quarter and interpret the changes in the nowcast with increasing precision, highlighting the importance of closely monitoring and continuously updating the outlook of the economy via the real-time data flow.

6. CONCLUSION

In this review, we illustrate the application of recent statistical techniques for the construction of an automated platform to process the real-time data flow—nowcasting, which we place in the context of various approaches developed over time to monitor and measure economic conditions. Nowcasting is a relatively new field in time-series econometrics, and it is likely to continue to develop on many fronts.

First, jointly modeling macroeconomic and financial conditions would provide an interface between finance and the macroeconomy. This would present a coherent framework to study the mechanisms through which macroeconomic news is transmitted to financial markets. Furthermore, it would allow us to go beyond the prediction of the central tendency toward nowcasting vulnerabilities and risks to the outlook, along the lines of the work of Adrian et al. (2016).

Second, nowcasting can be developed in a structural environment. Giannone et al. (2016) propose a nowcasting framework for a dynamic stochastic general equilibrium model. A benefit of this analysis is that it would allow researchers to compute real-time estimates of model-based variables that are not directly observable, such as the output gap (which captures the difference between actual GDP and its potential value) and the natural rate of interest. Reading the data flow through the lens of a structural model would also make it possible to identify meaningful shocks to the economy in real time.

Third, while our model makes use of big data with the traditional data sets that macroeconomists have long analyzed, new sources of big data, such as web searches, electronic transactions, and textual analyses, offer a timely glimpse into economic activity. The value of such data has been demonstrated in monitoring the economy in the absence of reliable data from statistical agencies, as well as in providing early estimates of economic indicators in particular sectors and geographic regions. However, further studies are needed to determine whether these alternative data could be integrated with the current array of economic data for the purpose of macroeconomic nowcasting.

Finally, it is important to continue to refine the communication and sharing of nowcasting, a step that the Federal Reserve Bank of New York has taken by publishing weekly updates of this model on its public website (**https://www.newyorkfed.org/research/policy/nowcast**). This will foster interaction with other analysts and forecasters and help maintain the development of the model attuned to changes in market practices.

DISCLOSURE STATEMENT

D.G. is a passive shareholder of Now-Casting Ltd., a web-based forecasting company.

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